

```
In [1]: import numpy as np
import pandas as pd

In [2]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
from matplotlib import style
from sklearn.metrics import accuracy_score
import warnings
warnings.filterwarnings('ignore')
from sklearn.naive_bayes import MultinomialNB, BernoulliNB
from sklearn.metrics import classification_report
from sklearn import metrics

In [3]: df=pd.read_csv('Stress-lysis.csv')
df.head()
```

```
Out[3]:
```

	Humidity	Temperature	Step_count	Stress_Level
0	21.33	80.33	123	1
1	21.41	80.41	93	1
2	27.12	86.12	196	2
3	27.64	86.64	177	2
4	10.87	79.87	87	0

```
In [4]: df.shape
Out[4]: (2801, 4)
```

```
In [5]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2801 entries, 0 to 2000
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype  
---  --
 0   Humidity      2801 non-null    float64
 1   Temperature   2801 non-null    float64
 2   Step_count    2801 non-null    int64  
 3   Stress_Level  2801 non-null    int64  
dtypes: float64(2), int64(2)
memory usage: 62.7 KB
```

```
In [6]: df.describe()
```

```
Out[6]:
```

	Humidity	Temperature	Step_count	Stress_Level
count	2001.000000	2001.000000	2001.000000	2001.000000
mean	20.000000	89.000000	100.141429	1.104448
std	5.777833	5.777833	58.182948	0.771094
min	10.000000	79.000000	0.000000	0.000000
25%	15.000000	84.000000	50.000000	0.000000
50%	20.000000	89.000000	101.000000	1.000000
75%	25.000000	94.000000	150.000000	2.000000
max	30.000000	99.000000	200.000000	2.000000

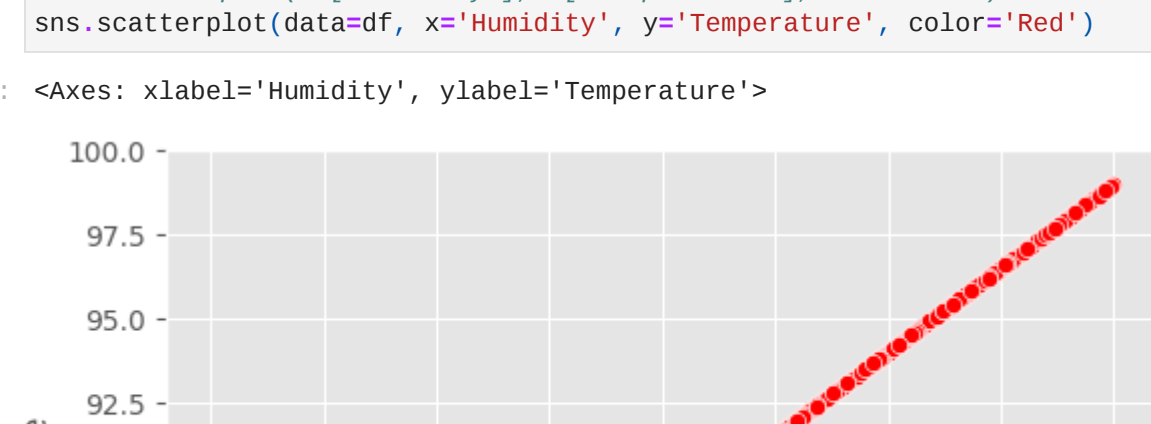
```
In [7]: df['Stress_Level'].unique()
Out[7]: array([1, 2, 0], dtype=int64)
```

```
In [8]: #style.use('ggplot')
sns.countplot(df['Stress_Level'])

import matplotlib.pyplot as plt
import seaborn as sns
# set the ggplot style
plt.style.use('ggplot')

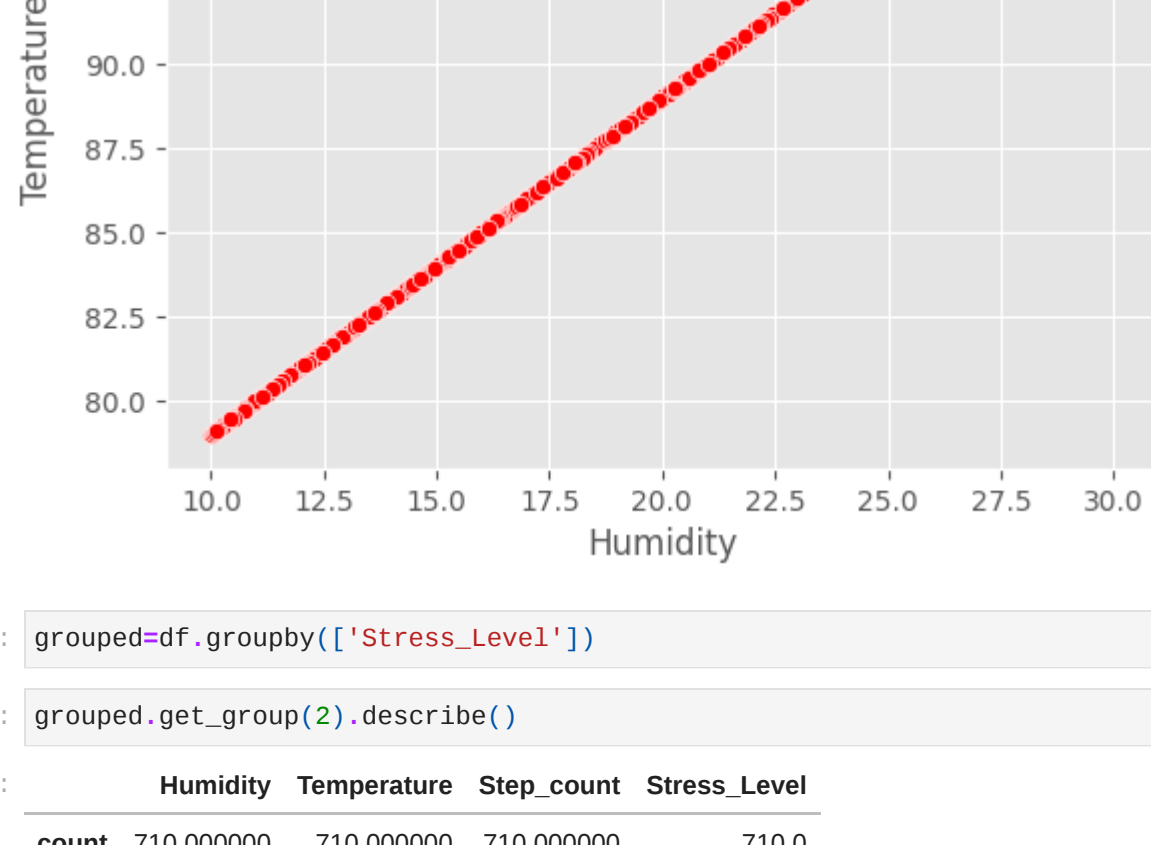
# create the count plot
sns.countplot(df['Stress_Level'])

# show the plot
plt.show()
```



```
In [9]: #sns.scatterplot(df['Humidity'],df['Temperature'],color='Red')
sns.scatterplot(data=df, x='Humidity', y='Temperature', color='Red')

Out[9]: <Axes: xlabel='Humidity', ylabel='Temperature'>
```



```
In [10]: grouped=df.groupby(['Stress_Level'])

In [11]: grouped.get_group(2).describe()
```

```
Out[11]:
```

	Humidity	Temperature	Step_count	Stress_Level
count	710.000000	710.000000	710.000000	710.0
mean	26.455000	95.455000	165.000000	2.0
std	2.051036	2.051036	20.508349	0.0
min	22.910000	91.910000	130.000000	2.0
25%	24.682500	93.682500	147.000000	2.0
50%	26.455000	95.455000	165.000000	2.0
75%	28.227500	97.227500	183.000000	2.0
max	30.000000	99.000000	200.000000	2.0

```
In [12]: #df.groupby(['Step_count'])['Step_count','Stress_Level'].describe()
df.groupby(['Step_count'])['Stress_Level'].describe()
```


```
Out[12]:
```

		Step_count					Stress_Level									
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max
Step_count																
0	100	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100	0.4	0.516398	0.0	0.0	0.0	1.0	1.0
1	100	1.0	0.0	1.0	1.0	1.0	1.0	1.0	100	0.4	0.516398	0.0	0.0	0.0	1.0	1.0
2	100	2.0	0.0	2.0	2.0	2.0	2.0	2.0	100	0.4	0.516398	0.0	0.0	0.0	1.0	1.0
3	100	3.0	0.0	3.0	3.0	3.0	3.0	3.0	100	0.4	0.516398	0.0	0.0	0.0	1.0	1.0
4	100	4.0	0.0	4.0	4.0	4.0	4.0	4.0	100	0.4	0.516398	0.0	0.0	0.0	1.0	1.0
...
196	100	196.0	0.0	196.0	196.0	196.0	196.0	196.0	100	2.0	0.000000	2.0	2.0	2.0	2.0	2.0
197	100	197.0	0.0	197.0	197.0	197.0	197.0	197.0	100	2.0	0.000000	2.0	2.0	2.0	2.0	2.0
198	100	198.0	0.0	198.0	198.0	198.0	198.0	198.0	100	2.0	0.000000	2.0	2.0	2.0	2.0	2.0
199	100	199.0	0.0	199.0	199.0	199.0	199.0	199.0	100	2.0	0.000000	2.0	2.0	2.0	2.0	2.0
200	100	200.0	0.0	200.0	200.0	200.0	200.0	200.0	100	2.0	0.000000	2.0	2.0	2.0	2.0	2.0

201 rows x 16 columns

```
In [13]: sns.heatmap(df.corr(),cmap='Greens_r',annot=True,square=True)

Out[13]: <Axes: >
```



```
In [14]: x=df.iloc[:,1:4]
y=df.iloc[:,4:5]
x.shape,y.shape

Out[14]: ((2801, 3), (2801,))
```

```
In [15]: xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.20,random_state=20)
xtrain.shape,xtest.shape,ytrain.shape,ytest.shape

Out[15]: ((1680, 3), (401, 3), (1680, 1), (401,))
```

```
In [16]: from sklearn.linear_model import LogisticRegression
logreg=LogisticRegression(random_state=42)
logreg.fit(xtrain,ytrain)
```

```
Out[16]:
```

```
*      LogisticRegression
LogisticRegression(random_state=42)
```

```
In [17]: from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier(n_neighbors=24,metric='linkowski',p=2)
knn.fit(xtrain,ytrain)
```

```
Out[17]:
```

```
*      KNeighborsClassifier
KNeighborsClassifier(n_neighbors=24)
```

```
In [18]: from sklearn.svm import SVC
svc=SVC(kernel='linear', random_state=42)
svc.fit(xtrain,ytrain)
```

```
Out[18]:
```

```
*      SVC
SVC(kernel='linear', random_state=42)
```

```
In [19]: #Decision Tree Algo
from sklearn.tree import DecisionTreeClassifier
dectree=DecisionTreeClassifier(criterion='entropy', random_state=42)
dectree.fit(xtrain,ytrain)
```

```
Out[19]:
```

```
*      DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=42)
```

```
In [20]: #Random Forest Algo
from sklearn.ensemble import RandomForestClassifier
ranfor=RandomForestClassifier(n_estimators=11,criterion='entropy', random_state=42)
ranfor.fit(xtrain,ytrain)
```

```
Out[20]:
```

```
*      RandomForestClassifier
RandomForestClassifier(criterion='entropy', n_estimators=11, random_state=42)
```

```
In [21]: from sklearn.linear_model import SGDClassifier
sgd=SGDClassifier(loss='hinge',shufle=True,random_state=101)
sgd.fit(xtrain,ytrain)
```

```
Out[21]:
```

```
*      SGDClassifier
SGDClassifier(random_state=101)
```

```
In [22]: MNB = MultinomialNB()
BNB = BernoulliNB()
SVM = SVC()
MNB.fit(xtrain, ytrain)
BNB.fit(xtrain, ytrain)
SVM.fit(xtrain, ytrain)
pred_mnb = MNB.predict(xtest)
pred_bnb = BNB.predict(xtest)
pred_svm = SVM.predict(xtest)
```

```
In [23]: # Multinomial Accuracy
print("Multinomial Accuracy: {accuracy_score(ytest, pred_mnb)}")
print(classification_report(ytest, pred_mnb))
print("MSE:", metrics.mean_absolute_error(ytest, pred_mnb))
print("MSE:", metrics.mean_squared_error(ytest, pred_mnb))
print("Root MSE:", np.sqrt(metrics.mean_squared_error(ytest, pred_mnb)))

Multinomial Accuracy: 0.73204887898509
precision    recall  f1-score   support

0      0.61      0.66      0.63      99
1      0.78      0.50      0.58     158
2      0.88      1.00      0.89     144

accuracy          0.72          0.72          0.72      401
macro avg          0.72          0.72          0.72      401
weighted avg          0.71          0.72          0.70      401

MSE: 0.2817955112219451
MSE: 0.2817955112219451
Root MSE: 0.53084149548629
```

```
In [24]: # Bernoulli Accuracy
print("Bernoulli Accuracy: {accuracy_score(ytest, pred_bnb)}")
print(classification_report(ytest, pred_bnb))
print("MSE:", metrics.mean_absolute_error(ytest, pred_bnb))
print("MSE:", metrics.mean_squared_error(ytest, pred_bnb))
print("Root MSE:", np.sqrt(metrics.mean_squared_error(ytest, pred_bnb)))

Bernoulli Accuracy: 0.3940149625935162
precision    recall  f1-score   support

0      0.00      0.00      0.00      99
1      0.30      1.00      0.57     158
2      0.00      0.00      0.00     144

accuracy          0.39          0.39          0.40      401
macro avg          0.13      0.33      0.19      401
weighted avg          0.16      0.30      0.22      401

MSE: 0.605959374084838
MSE: 0.605959374084838
Root MSE: 0.7784584878016041
```

```
In [25]: # SVM Accuracy
print("SVM Accuracy: {accuracy_score(ytest, pred_svm)}")
print(classification_report(ytest, pred_svm))
print("MSE:", metrics.mean_absolute_error(ytest, pred_svm))
print("MSE:", metrics.mean_squared_error(ytest, pred_svm))
print("Root MSE:", np.sqrt(metrics.mean_squared_error(ytest, pred_svm)))

SVM Accuracy: 0.99786234139861
precision    recall  f1-score   support

0      1.00      1.00      1.00      99
1      0.99      1.00      1.00     158
2      1.00      0.99      1.00     144

accuracy          1.00          1.00          1.00      401
macro avg          1.00          1.00          1.00      401
weighted avg          1.00          1.00          1.00      401

MSE: 0.0024937655860349127
MSE: 0.0024937655860349127
Root MSE: 0.04993761694389223
```

```
In [26]: # Logistic Regression
Y_pred_logreg = logreg.predict(xtest)
accuracy_logreg = accuracy_score(ytest, Y_pred_logreg)
print("Logistic Regression: " + str(accuracy_logreg * 100))
print(classification_report(ytest, Y_pred_logreg))
from sklearn import metrics
print("Mean Absolute Error:", metrics.mean_absolute_error(ytest, Y_pred_logreg))
print("Mean Squared Error:", metrics.mean_squared_error(ytest, Y_pred_logreg))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(ytest, Y_pred_logreg)))

Logistic Regression: 100.0
precision    recall  f1-score   support

0      1.00      1.00      1.00      99
1      1.00      1.00      1.00     158
2      1.00      1.00      1.00     144

accuracy          1.00          1.00          1.00      401
macro avg          1.00          1.00          1.00      401
weighted avg          1.00          1.00          1.00      401

Mean Absolute Error: 0.0
Mean Squared Error: 0.0
Root Mean Squared Error: 0.0
```

```
In [27]: # Linear Regression
from sklearn.linear_model import LinearRegression
lreg = LinearRegression().fit(xtrain, ytrain)
Y_pred_lreg = lreg.predict(xtest)
accuracy_lreg = accuracy_score(ytest, Y_pred_lreg, round())
print("Linear Regression: " + str(accuracy_lreg * 100))
from sklearn import metrics
print("Mean Absolute Error:", metrics.mean_absolute_error(ytest, Y_pred_lreg))
print("Mean Squared Error:", metrics.mean_squared_error(ytest, Y_pred_lreg))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(ytest, Y_pred_lreg)))

Linear Regression: 98.7531172868254
Mean Absolute Error: 0.2346212489540908
Mean Squared Error: 0.87473848087890818
Root Mean Squared Error: 0.27336876353930694
```

```
In [28]: # LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
lda = LinearDiscriminantAnalysis().fit(xtrain, ytrain)
Y_pred_lda = lda.predict(xtest)
accuracy_lda = accuracy_score(ytest, Y_pred_lda)
print("LinearDiscriminantAnalysis: " + str(accuracy_lda * 100))
print(classification_report(ytest, Y_pred_lda))
from sklearn import metrics
print("Mean Absolute Error:", metrics.mean_absolute_error(ytest, Y_pred_lda))
print("Mean Squared Error:", metrics.mean_squared_error(ytest, Y_pred_lda))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(ytest, Y_pred_lda)))

LinearDiscriminantAnalysis: 97.8074812967581
precision    recall  f1-score   support

0      0.93      1.00      0.97      99
1      1.00      0.92      0.96     158
2      0.97      1.00      0.98     144

accuracy          0.97          0.97          0.97      401
macro avg          0.97          0.97          0.97      401
weighted avg          0.97          0.97          0.97      401

Mean Absolute Error: 0.02929327832418952
Mean Squared Error: 0.02929327832418952
Root Mean Squared Error: 0.17289897951146758
```

```
In [29]: # Ridge
from sklearn.linear_model import Ridge
clf = Ridge(alpha=1.0)
#fitting the classifier into training set
clf.fit(xtrain,ytrain)
Y_pred_clfidf = clf.predict(xtest)
accuracy_clfidf = accuracy_score(ytest, Y_pred_clfidf, round())
print("Ridge: " + str(accuracy_clfidf * 100))
from sklearn import metrics
print("Mean Absolute Error:", metrics.mean_absolute_error(ytest, Y_pred_clfidf))
print("Mean Squared Error:", metrics.mean_squared_error(ytest, Y_pred_clfidf))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(ytest, Y_pred_clfidf)))

Ridge: 98.7531172868254
Mean Absolute Error: 0.23462124895408276
Mean Squared Error: 0.8747382030523295
Root Mean Squared Error: 0.2733684161532802
```

```
In [30]: # Lasso
from sklearn.linear_model import Lasso
clf=Lasso(alpha=1.0)
#fitting the classifier into training set
clf.fit(xtrain,ytrain)
Y_pred_lassoclf = clf.predict(xtest)
accuracy_lasso = accuracy_score(ytest, Y_pred_lasso, round())
print("Lasso: " + str(accuracy_lasso * 100))
from sklearn import metrics
print("Mean Absolute Error:", metrics.mean_absolute_error(ytest, Y_pred_lasso))
print("Mean Squared Error:", metrics.mean_squared_error(ytest, Y_pred_lasso))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(ytest, Y_pred_lasso)))

Lasso: 77.3967331679823
Mean Absolute Error: 0.330379699697452
Mean Squared Error: 0.10874324889751705
Root Mean Squared Error: 0.437886162312223
```

```
In [31]: #K nearest neighbors
Y_pred_knn = knn.predict(xtest)
accuracy_knn = accuracy_score(ytest, Y_pred_knn)
print("K nearest neighbors: " + str(accuracy_knn * 100))
print(classification_report(ytest, Y_pred_knn))
from sklearn import metrics
print("Mean Absolute Error:", metrics.mean_absolute_error(ytest, Y_pred_knn))
print("Mean Squared Error:", metrics.mean_squared_error(ytest, Y_pred_knn))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(ytest, Y_pred_knn)))

K nearest neighbors: 99.75062344139651
precision    recall  f1-score   support

0      1.00      1.00      1.00      99
1      0.99      1.00      1.00     158
2      1.00      0.99      1.00     144

accuracy          1.00          1.00          1.00      401
macro avg          1.00          1.00          1.00      401
weighted avg          1.00          1.00          1.00      401

Mean Absolute Error: 0.0024937655860349127
Mean Squared Error: 0.0024937655860349127
Root Mean Squared Error: 0.04993761694389223
```

```
In [32]: # SVC( Support Vector Classifier)
Y_pred_svc = svc.predict(xtest)
accuracy_svc = accuracy_score(ytest, Y_pred_svc)
print("Support Vector Classifier: " + str(accuracy_svc * 100))
print(classification_report(ytest, Y_pred_svc))
from sklearn import metrics
print("Mean Absolute Error:", metrics.mean_absolute_error(ytest, Y_pred_svc))
print("Mean Squared Error:", metrics.mean_squared_error(ytest, Y_pred_svc))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(ytest, Y_pred_svc)))

Support Vector Classifier: 100.0
precision    recall  f1-score   support

0      1.00      1.00      1.00      99
1      1.00      1.00      1.00     158
2      1.00      1.00      1.00     144

accuracy          1.00          1.00          1.00      401
macro avg          1.00          1.00          1.00      401
weighted avg          1.00          1.00          1.00      401

Mean Absolute Error: 0.0
Mean Squared Error: 0.0
Root Mean Squared Error: 0.0
```

```
In [33]: # Decision Tree
Y_pred_dectree = dectree.predict(xtest)
accuracy_dectree = accuracy_score(ytest, Y_pred_dectree)
print("Decision tree: " + str(accuracy_dectree * 100))
print(classification_report(ytest, Y_pred_dectree))
from sklearn import metrics
print("Mean Absolute Error:", metrics.mean_absolute_error(ytest, Y_pred_dectree))
print("Mean Squared Error:", metrics.mean_squared_error(ytest, Y_pred_dectree))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(ytest, Y_pred_dectree)))

Decision tree: 100.0
precision    recall  f1-score   support

0      1.00      1.00      1.00      99
1      1.00      1.00      1.00     158
2      1.00      1.00      1.00     144

accuracy          1.00          1.00          1.00      401
macro avg          1.00          1.00          1.00      401
weighted avg          1.00          1.00          1.00      401

Mean Absolute Error: 0.0
Mean Squared Error: 0.0
Root Mean Squared Error: 0.0
```

```
In [34]: # Random Forest
Y_pred_ranfor = ranfor.predict(xtest)
accuracy_ranfor = accuracy_score(ytest, Y_pred_ranfor)
print("Random Forest: " + str(accuracy_ranfor * 100))
print(classification_report(ytest, Y_pred_ranfor))
from sklearn import metrics
print("Mean Absolute Error:", metrics.mean_absolute_error(ytest, Y_pred_ranfor))
print("Mean Squared Error:", metrics.mean_squared_error(ytest, Y_pred_ranfor))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(ytest, Y_pred_ranfor)))

Random Forest: 100.0
precision    recall  f1-score   support

0      1.00      1.00      1.00      99
1      1.00      1.00      1.00     158
2      1.00      1.00      1.00     144

accuracy          1.00          1.00          1.00      401
macro avg          1.00          1.00          1.00      401
weighted avg          1.00          1.00          1.00      401

Mean Absolute Error: 0.0
Mean Squared Error: 0.0
Root Mean Squared Error: 0.0
```

```
In [35]: #SGD(Stochastic Gradient Classifier)
Y_pred_sgd = sgd.predict(xtest)
accuracy_sgd = accuracy_score(ytest, Y_pred_sgd)
print("Stochastic Gradient Classifier: " + str(accuracy_sgd * 100))
print(classification_report(ytest, Y_pred_sgd))
from sklearn import metrics
print("Mean Absolute Error:", metrics.mean_absolute_error(ytest, Y_pred_sgd))
print("Mean Squared Error:", metrics.mean_squared_error(ytest, Y_pred_sgd))
print("Root Mean Squared Error:", np.sqrt(metrics.mean_squared_error(ytest, Y_pred_sgd)))

Stochastic Gradient Classifier: 97.0862341398609
precision    recall  f1-score   support

0      1.00      0.95      0.97      99
1      0.96      0.98      0.97     158
2      0.98      0.99      0.98     144

accuracy          0.98          0.97          0.98      401
macro avg          0.98          0.97          0.98      401
weighted avg          0.98          0.98          0.98      401
```


Mean Absolute Error: 0.02493765586894913
Mean Squared Error: 0.02493765586894913
Root Mean Squared Error: 0.15791651046371636